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FIRM GROWTH AND PRODUCTIVITY GROWTH: EVIDENCE FROM A PANEL VAR

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Abstract

This paper offers new insights into the processes of firm growth by applying a reduced-form vector autoregression (VAR) model to longitudinal panel data on French manufacturing firms. We observe the co-evolution of key variables such as growth of employment, sales, and gross operating surplus, as well as growth of multifactor productivity. It seems that employment growth is negatively associated with subsequent growth of productivity. This latter result, however, is sensitive to our choice of productivity indicator, i.e. multifactor productivity or labour productivity.

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1 Introduction

The aim of this paper is to gain new insights into the relationship between firm growth and productivity growth. Whilst theoretical contributions have not been silent upon this topic (see the survey in Section 2), the propositions that have been put forward are far from harmonious. A sparse empirical literature, however, seems to suggest that firm growth and productivity growth are only weakly associated with each other.

A major difficulty affecting both theoretical and empirical work is the inherent endogeneity in the relationship between firm growth and productivity growth. Theoretical work has provided arguments why growth may affect productivity, but also they suggest that productivity may affect growth. Theoretical propositions have been discordant and conflicting, however, suggesting that progress in this field needs to be resolved by empirical work. The analysis in this paper distinguishes itself from the previous studies by focusing on modeling the co-evolution of firm growth and productivity growth. In addition, we view firm growth as a multidimensional phenomenon, distinguishing between employment growth, sales growth, and growth of profits. We suggest that this conception of the growing firm as a dynamic co-evolving system of interdependent variables is best described in the context of a vector autoregression (VAR) model.

Our analysis indicates that employment growth is associated with a subsequent decrease in multifactor productivity. Sales growth appears to have a statistically significant contribution to subsequent changes in productivity, although this effect is rather small. Our results also indicate that productivity growth does not seem to be followed by much employment growth or sales growth.

The structure of the paper is as follows. We begin by surveying the literature on firm growth and productivity (Section 2). In Section 3 we present the database, we describe how we computed the productivity variable, and then we present some summary statistics. In Section 4 we discuss our regression methodology. In Section 5 we present our main results, and explore the reliability of these estimates in Section 6. Section 7 concludes.

2 Literature review

Theoretical contributions An early discussion of the subject can be found in Penrose (1959), who suggested that firm growth leads to decreases in productivity above a certain growth rate (this is popularly known as the 'Penrose effect'). Since the planning and realization of growth projects places additional demands on a firm's managerial resources, these managers will be distracted from their task of keeping operating costs down. As a result, firm growth may lead to a decrease in productivity. Of particular interest to our present inquiry is Penrose's proposition that it is specifically the hiring of new employees that is responsible for decreases in productivity, as managerial attention is redirected to the training and internalization of new managers.

In contrast, the Kaldor-Verdoorn concept of 'dynamic increasing returns' can be applied at the firm level, and would predict that firm growth is positively associated with productivity growth (see McCombie, 1987). Expanding firms may invest in new technologies and learn about more efficient methods of production. Their expansion may also be associated with increases in productivity if their growth of output feeds off latent organizational slack.

Another branch of theoretical work focuses on the other causal direction – that is, the influence of productivity on firm expansion (see, e.g., Alchian, 1950; Metcalfe, 1994). This body of literature invokes the evolutionary principle of 'growth of the fitter' to explain that the more productive firms should thrive whilst the least productive firms will lose market share, and eventually exit the market.

Empirical studies Empirical studies have also tried to tackle the relationship between firm growth and productivity growth. Many studies have focused on the associations between productivity and firm growth, and thus do not attempt to decompose the net effect into the contribution of growth to productivity, or the contribution of productivity to growth. Baily et al. (1996) observe that, among plants with increasing labour productivity between 1977 and 1987, firms that grew in terms of employees were balanced out by firms that decreased employment. They find that about a third of labour productivity growth is attributable to growing firms, about a third to downsizing firms, and the remaining third is attributable to the processes of entry and exit. Similarly, Foster et al. (1998) fail to find a robust significant relationship between establishment-level labour productivity or multifactor productivity and growth (see also the review in (Bartelsman and Doms, 2000, pp. 583-584). In addition, using a database of Italian manufacturing firms, Bottazzi et al. (2002) fail to find a robust relationship between productivity and growth (for discussions see also Dosi, 2007; Coad, 2007b). Furthermore, evidence from UK manufacturing plants reveals a slightly negative between-effect in allocation of market share between firms according to productivity, over a time scale of 6 years (Disney et al., 2003, p. 683).

An alternative approach is that of Power (1998), who investigates whether new investment (e.g. in recent capital vintages) is associated with subsequent productivity increases, for US manufacturing plants. As a consequence, Power's work can be seen as an investigation of the contribution of growth of capital[1] to growth of productivity. Oddly enough, the expected link between new investment and productivity growth appears to be largely absent.

Previous research into the link between productivity growth has come up against a number of limitations, however, which motivates the present investigation. First, almost all of the studies reviewed above focus only on contemporaneous associations of productivity growth, and therefore neglect any dynamic considerations (i.e. time lags) affecting the relationship between firm growth and productivity growth. Second, firm growth is

[1]Note however that her analysis does not distinguish between expansionary investment and replacement investment.

indeed a multifaceted phenomenon, with each indicator of firm growth (such as employment or sales) having its drawbacks. In this study we include several indicators of firm growth and explore their specific roles in the process of firm-level productivity growth. Third, we explore the robustness of our results along a number of dimensions, concerning the number of lags in our regression specification and the choice of productivity growth indicator. In addition, we repeat our analysis at a disaggregated (sectoral) level to investigate how productivity dynamics vary across heterogeneous industries. Fourth, while previous work has invariably focused on 'the average effect for the average firm', we apply semi-parametric quantile regression techniques to investigate how the relationship between firm growth and productivity growth varies for growing and declining firms.

3 Database construction

3.1 Data

Our analysis draws upon the EAE databank collected by SESSI and provided by the French Statistical Office (INSEE).[2][3] This database contains longitudinal data on a virtually exhaustive panel of French firms with 20 employees or more over the period 1989-2004. We restrict our analysis to the manufacturing sectors.[4] For statistical consistency, we only utilize the period 1996-2004 and we consider only continuing firms over this period. Firms that entered midway through 1996 or exited midway through 2004 have been removed. Since we want to focus on internal, 'organic' growth rates, we exclude firms that have undergone any kind of modification of structure, such as merger or acquisition.

[2]The EAE databank has been made available to Alex Coad under the mandatory condition of censorship of any individual information.

[3]This database has already featured in several other studies into firm growth – see Bottazzi et al. (2008), Coad (2007c), and Coad (2007a).

[4]More specifically, we examine firms in the two-digit NAF sectors 17-36, where firms are classified according to their sector of principal activity (the French NAF classification matches with the international NACE and ISIC classifications). We do not include NAF sector 37, which corresponds to recycling industries.

In order to avoid misleading values and the generation of NANs[5] whilst taking logarithms and ratios, we now retain only those firms with strictly positive values for Gross Operating Surplus (GOS),[6] Value Added (VA), and employees in each year. This creates some additional missing values, and as a consequence may well limit the degree to which the results obtained with the present sample can be generalized to other groups of firms.

In keeping with previous studies, our measure of growth rates is calculated by taking the differences of the logarithms of size:

$$GROWTH_{it} = log(SIZE_{it}) - log(SIZE_{i,t-1}) \tag{1}$$

where, to begin with, $SIZE$ is measured in terms of employment, sales, or gross operating surplus for firm i at time t.

To measure productivity growth, we use a non-parametric multi-factor productivity index, which is now presented in detail.

3.2 Performance analysis

One of the most popular ways to estimate a firm's performance is to compare to other, similar, firms. There are several methods available to compute this 'relative' (relative to the group of reference firms) performance. In this paper we use the nonparametric order-m frontier approach by Cazals et al. (2002) which is closely related to the well-known Free Disposal Hull (FDH) analysis and shares most of its properties. For example, there is no need to specify a functional relationship between the input and output space ex-ante and multiple input and output scenarios can easily be handled. No universal production function is moreover assumed. The production functions are non-convex and can differ between firms. In contrast to the FDH approach the order-m frontier analysis is less

[5]NAN is shorthand for Not a Number, which refers to the result of a numerical operation, which cannot return a valid number value. In our case, we may obtain a NAN if we try to take the logarithm of a negative number, or if we try to divide a number by zero.

[6]GOS is sometimes referred to as 'profits' in the following.

sensitive to noise and outliers in the data. For an extensive treatment of this issue see Daraio and Simar (2007).

In nonparametric frontier analyses firms are compared to best-practice firms which form a performance frontier. The distance to the frontier represents a firm's (in-) efficiency level.

The idea of the order-m approach is the following: in contrast to the traditional methods the transformation of inputs into outputs is seen as a probabilistic process. The interest is in the probability with which an observation is dominated by other observations. According to Cazals et al. (2002), the benchmark (frontier) of an observation i can be the expected minimum achievable input-level among m firms, drawn randomly (with replacement) from the population of all firms showing at minimum the output level of the considered firms i.[7] As it is common we estimate firms' performance in an input-orientation (Scheel, 2000). Hereby cost reduction potentials (reduction of input factors) are identified.

Changes in firms' performance over time are commonly evaluated by the Malmquist index proposed by Caves et al. (1982) and extended to a multiple input and output scenarios in nonparametric frontier analysis by Färe et al. (1992, 1994). Based on this Wheelock and Wilson (2003) transferred this idea to the order-m approach.

The Malmquist index captures the change in the performance of a firm between two periods of time. However, the change can be cause by various effects. Because of the data used, it is reasonable not to use the 'complete' Malmquist index (which can be interpreted as change in total factor productivity) as productivity change measure. It is common to decompose the index into a number of components (see for an overview Zofio, 2006). For the purpose of this paper the decomposition of the order-m Malmquist index by Wheelock and Wilson (2003) into four different parts is especially valuable. We focus on only

[7] m denotes the size of the sub-sample that is drawn. For choosing an appropriate value for m we follow Bonaccorsi et al. (2004) in that not more than about ten percent of the units are outside the frontier. Here, this is true for $m = 1500$.

one of the four components, namely the measure of the change in the order-m *technical* efficiency $\triangle M\_Eff$. It estimates the 'movement' of a firm relative to the performance frontier and shows whether the firm was able to decrease / increase its technological gap (catching-up or falling behind) to the order-m best-practice firms. This measure is included as a variable approximating change (growth) in the multifactor productivity. In the context of the paper scale economies or the movements of the frontier function over time are less interesting for which we don't analyze the impact of the other three components (see Appendix 8 and Wheelock and Wilson (2003) for more details).

We generate the multifactor productivity growth variable using four inputs and two outputs. The inputs are total fixed assets, total intangible assets, the average number of employees, and the total wage bill. The outputs are total sales and value added.

We also compare the results obtained using this multifactor productivity indicator with results obtained from an alternative productivity growth variable – i.e. the well-known 'labour productivity' indicator (defined simply as value-added divided by number of employees). Regression results using labour productivity are reported in Section 5.2, although for a more detailed analysis of the role of labour productivity in firm growth processes see Coad (forthcoming).

3.3 Summary statistics

Table 1 presents some summary statistics, which provide the reader with a rough idea of the range of firm sizes in our data set. Summary statistics for growth rate series are in Table 2. Note that the growth rate series are all normalized to having a zero mean. This effectively removes the influence of inflation and other macroeconomic trends.

Table 3 shows the correlations between the growth rate indicators and the productivity indicator.[8] Spearman's rank correlation coefficients are also shown since these are more

[8] It is known that DEA performance scores are serially correlated making standard approaches to inference invalid (Simar and Wilson, 2007). Even though Simar and Wilson (2007) only concentrate on the traditional DEA approach, it is clear that order-m efficiency scores and the related Malmquist indices are

robust to outliers. We observe that, as expected, our non-parametric productivity growth variable is positively correlated with the contemporaneous growth of sales (an output) and of profits, and negatively correlated with the growth of employment (an input). Furthermore, productivity growth is positively associated with the contemporaneous growth of GOS.

All of the series are correlated between themselves at levels that are highly significant. However, the correlations are indeed far from perfect, as has been noted elsewhere (Delmar et al., 2003). A certain amount of sales growth and GOS growth appears to be contemporaneous. These two variables are not so well correlated with employment growth, however. The correlation coefficient between GOS growth and employment growth, for example, is only 0.0671 (with a Spearman's rank correlation coefficient of 0.0710).

Although there is much collinearity between these series, the lack of persistence in firm growth rates (despite a high degree of persistence of firm size) will, we hope, aid in identification. Furthermore, the large number of observations will also be helpful in identification.

Figure 1 shows that the growth rates distributions are fat-tailed, and do not resemble the Gaussian case. Instead, the 'tent-shape' that we observe on the log-log plots resembles the Laplace or 'symmetric exponential' distribution.[9] This gives an early hint that OLS estimators, which assume Gaussian residuals, may perform less well than Least Absolute Deviation (LAD) techniques.

serially correlated as well. However, to the authors' knowledge a method that allows to deal with this problem has not been developed in the context of the analysis conducted in this paper. Lacking an acceptable solution we use the obtained scores as they are.

[9]The distribution of productivity growth appears to be positively skewed, which could be an artefartifactact of the truncation of the lowest values during the construction of the productivity variable.

4 Methodology

Introducing the VAR The regression equation of interest is of the following form:

$$w_{it} = c + \beta w_{i,t-1} + \varepsilon_{it} \tag{2}$$

where w_{it} is an $m \times 1$ vector of random variables for firm i at time t. β corresponds to an $m \times m$ matrix of slope coefficients that are to be estimated. In our particular case, m=4 and corresponds to the vector (GOS growth(i,t), Sales growth (i,t), Empl growth (i,t), productivity growth(i,t))'. ε is an $m \times 1$ vector of disturbances. Since previous work on this data set has not observed any dependence of growth on size (Bottazzi et al., 2008), we do not clean the series of size dependence before applying the VAR.[10]

Our regression equation does not include industry dummy variables, because we anticipate that the inclusion of dummies will not be an effective way of exploring differences in the complex interactions at work in the growth patterns of firms in different sectors. Instead, in what follows we repeat the analysis at the level of individual industries (see Section 6.3).

We could estimate equation (2) via 'reduced-form' VARs,[11] which for example could correspond to a series of m individual OLS regressions (Stock and Watson, 2001). One problem with OLS regressions in this particular case, however, is that the distribution of firm growth rates is typically exponentially distributed and has much heavier tails than the Gaussian. In this case OLS may provide unreliable results, and as argued in Bottazzi et al. (2008) we prefer Least Absolute Deviation (LAD) estimation.

Since our analysis focuses on growth rates (i.e. differences rather than levels) we do not need to address the issue of unobserved heterogeneity in the form of possible time-

[10] It is also of interest to observe that Wilson and Williams (2000) also find that growth rates are independent of size in their analysis of the growth of French banks.

[11] These reduced-form VARs do not impose any *a priori* causal structure on the relationships between the variables, and are therefore suitable for the preliminary nature of our analysis.

invariant firm-specific effects.

We also base our inference upon standard errors obtained using the computationally intensive 'bootstrapping' resampling technique (see Efron and Gong (1983) for an introduction).

Causality or association? Our intentions in this paper are to summarize the co-movements of the growth series. We remind the reader of the important distinction between correlation and causality. The discussion in Section 2 has shown how theoretical intuitions on the relationship between firm growth and productivity growth have been far from conclusive. As a result, we do not incorporate theoretical propositions into our empirical framework in an attempt to assist structural identification of the underlying causality. Instead, at this relatively early stage, we prefer to describe the lead-lag associations between the variables.

5 Aggregate Analysis

5.1 Multifactor productivity

The regression results are presented in Tables 4 and 5. A first observation is that all of the series (apart from employment) exhibit negative autocorrelation – this is shown along the diagonals of the coefficient matrices for the lags. This is in line with previous work. We also observe that the LAD estimates for the autocorrelation coefficients are lower than those obtained using OLS (This was also observed in Bottazzi et al. (2008) and is explored in Coad (2007a)). The autocorrelation coefficients for GOS growth and productivity growth display a particularly large (negative) magnitude. Although a substantial previous literature has emphasized the 'persistence of profits',[12] the *growth* of profits has little persistence.

[12] See amongst others Mueller (1977), Goddard et al. (2006) and Gschwandtner (2005).

In the following we will base our comments on our preferred specification, the bootstrapped LAD regression results in Table 5.

Employment growth seems to make a positive contribution to subsequent sales growth, although it makes no significant direct contribution to GOS growth. Growth of sales is strongly associated with subsequent GOS growth. On the other hand, GOS growth is associated with a relatively small subsequent growth of sales, and an even smaller growth of employment. Growth of profits may have a more persistent effect on employment growth than for sales growth, however. This general timeline of the firm growth process is in line with results in Coad (forthcoming) on French data and Coad and Rao (2009) on US data.

As could be expected, we find that productivity growth is positively related to the subsequent growth of profits. Nevertheless, we observe that productivity growth does not seem to be the main driver of either sales growth or employment growth. This is at odds with some interpretations of the evolutionary principle of 'growth of the fitter' that would expect productivity growth to be positively related with subsequent firm growth.[13]

Our estimates in Tables 4 - 5 do not provide a clear picture of how productivity growth affects subsequent growth of employment or sales. Basing ourselves on the results in Table 5, however, we suggest that productivity growth has a slight negative influence on subsequent employment growth and sales growth. This is consistent with the hypothesis that 'introverted' firms that focus on increasing their productivity have a lower propensity for expansion. We remain cautious about this interpretation, however, because our estimates are somewhat sensitive to the regression specification (as well as the alternative labour productivity indicator – see Section 5.2).

Finally, we observe the influence of our growth variables on subsequent productivity growth. One observation that appears to be fairly robust is that employment growth is negatively associated with subsequent growth of multifactor productivity. Sales growth,

[13] See Coad (2007c) for a discussion.

on the other hand, displays a relatively small positive association with subsequent productivity growth. These results suggest that firms that take on new employees are unable to rapidly convert these additional human resources into a corresponding increase in output (i.e. sales) that would be commensurate with the 'benchmark' productivity levels observed for other firms. It is also of interest to observe that, whilst productivity growth seems to make a positive contribution to subsequent GOS growth, GOS growth appears to make a negative contribution to subsequent productivity growth (although the magnitude is somewhat smaller). This is consistent with a behavioral / satisfying theory of firm performance, in which it takes time for productivity increases to be translated into financial performance, but once a firm's employees observe a successful growth of profits they react by reducing their effort levels, thus leading to a small decrease in productivity.

We also observe that the R^2 statistics are rather low, always lower than 10%. Empirical work into firm growth rates shows that R^2 statistics are typically low when growth rates are investigated, seldom rising above 10% and often much lower (see the summary in Coad (forthcoming) , Table 7.1). Previous work[14] on this database yielded R^2 values of between 2% and 10%, which is comparable to the results we obtain here. One possible explanation could be the lumpiness of growth rates (most firms have growth rates close to zero but a few firms grow very fast). It is therefore difficult to relate this heavy-tailed property of the dependent variable to other statistical series that are included as independent variables. Another possible explanation is that our regression specifications don't allow for contemporaneous effects - instead we impose a minimum one-year lag between the dependent variable and the independent variables. However, the contemporaneous correlations (shown in our Table 3) are quite large and suggest that the R^2 would be higher if contemporaneous effects were included. However, we cannot hide the fact that the vector autoregression specification does little to improve the R^2 statistic. This should be kept in mind in the present paper and investigated in further work.

[14] See for example Coad (2007a,c, 2008)

5.2 Labour productivity

Non-parametric productivity measurement techniques, such as used above, are a useful tool for analyzing firm performance even when we acknowledge that firms are fundamentally heterogeneous in their production processes (Cantner and Krueger, 2007). Our productivity indicator also has the advantage of including multiple inputs into a firm's production process, yielding a synthetic indicator of a firm's productive efficiency. One drawback of the indicator, however, is that it is not a very 'transparent' measure. We therefore repeat our analysis using an alternative productivity indicator – labour productivity. This well-known indicator of productivity levels is simply calculated as employment / value added. Growth of labour productivity is then calculated taking log-differences of productivity levels.

The results are presented in Table 6. These results are admittedly quite different from those in the previous results tables, in several cases, which suggests that alternative indicators of productivity capture different aspects of productivity growth. (Whilst our labour productivity variable simply measures value added per worker, the multifactor productivity indicator also takes into account the role of average wage, tangible and intangible assets, as well as scale effects.) Concerning our productivity variable, it seems that labour productivity growth has a small negative influence on subsequent employment growth, whilst being positively associated with subsequent sales growth and (of course) GOS growth. Whilst GOS growth is negatively associated with subsequent labour productivity growth, growth of employment and sales appear to have a positive correlation with this latter.

One puzzling result is that employment growth appears to be negatively related with subsequent growth of multifactor productivity whilst it appears to be positively related with subsequent growth of labour productivity. Coefficients for both variables are precisely estimated, relatively speaking, and are robust across several specifications.[15] It is

[15]See also Coad (forthcoming) for a robustness analysis concerning the labour productivity coefficient

unlikely that this discrepancy can be entirely attributed to measurement error or specification error. Where can this divergence come from? After all, labour productivity and multifactor productivity are often taken to reflect the same phenomenon. A first explanation is that, on average, firms that take on new employees lower their productivity by increasing the average wage. This is consistent with the well-known observation that larger firms pay higher wages (Brown and Medoff, 1989). Our multifactor productivity indicator takes into account average wages as well as number of employees, whereas the labour productivity indicator merely focuses on number of employees. Some preliminary regressions (not reported here) support this hypothesis, because they suggest that average wage (i.e. total wage bill/employees) does in fact rise following employment growth. A second possible explanation is that growing firms have a bias towards capital-intensive production methods. This is in accordance with another well-known observation about large firms – that they are more capital intensive than their smaller counterparts. It may be that growing firms add capital in larger proportions than they add employees. These new employees may not be able to use new capital efficiently upon arrival. As a result, although labour productivity may increase following employment growth, multifactor productivity will decrease because this latter indicator takes into account the efficiency with which capital is utilized.

6 Disaggregated analysis

6.1 Size disaggregation

Due care needs to be taken to deal with how growth dynamics vary with factors such as firm size. We cannot suppose that it will be meaningful to take a 'grand average' over a large sample of firms and assume that the coefficients obtained are a valid representation for all firms. Coad (2007a) shows how the time scale of growth processes varies between

estimates.

small and large firms. For example, whilst small firms display significant negative autocorrelation in annual growth rates, large firms experience positive autocorrelation which is consistent with the idea that they plan their growth projects over a longer time horizon. As a result, before we can feel confident about the robustness of our results, we should investigate the possible coexistence of different growth regimes for firms of different sizes.

We split our sample into 5 size groups, according to mean number of employees 1996-2004. The results are presented in Table 7. The task of sorting growing entities into size groups is not straightforward statistical task, however. In Table 8, therefore, we use an alternative methodology for sorting the firms into size groups (i.e. according to their sales in 1996).

Although similar patterns are observed in each of the size groups, we observe that the autocorrelation coefficients (along the diagonals) vary somewhat with size (more on this in Coad, 2007a).

Concerning productivity growth, we observe that GOS growth is negatively associated with subsequent productivity growth for small firms, although the sign of the association is positive for the larger firms. In contrast, sales growth appears to be positively associated with subsequent productivity growth in the case of small firms, whereas the sign is reversed for larger firms. These differential effects are visible in both size classification schemes. This is consistent with the following interpretation: small firms may first have to increase their total sales to reach a size where they can be more productive; larger firms, however, face no such pressure to grow and should instead focus on operating efficiency and the generation of profits. Employment growth is associated with subsequent decreases in productivity in all size groups, although this effect is never statistically significant for the largest group. We also find further (albeit weak) evidence that productivity has a negative influence on employment growth in the next period.

6.2 Temporal disaggregation

How does the relationship between firm growth and productivity growth vary over the business cycle? To investigate this, we repeat our analysis for individual years, and report the results in Table 9.

Although a certain degree of fluctuation can be observed in the coefficients, these results reinforce some of our earlier findings. We observe once again that employment growth is consistently associated with a decrease in productivity, and the coefficient is of a similar magnitude to that obtained in previous specifications. This effect is visible in every single year we investigate. Our other results concerning productivity growth are often statistically insignificant, although in the cases where they are significant they are similar to our previous results.

6.3 Sectoral disaggregation

One possibility that deserves investigation is that there may be a sector-specific element in the dynamics of firm growth. For example, the evolution of the market may be easier to foresee in some industries (e.g. technologically mature industries) than in others. Industries may also vary in relation to the importance of employment growth for the growth of output. We explore how our results vary across industries by loosely following Bottazzi et al. (2002), and comparing the results from four particular sectors: precision instruments, primary metals, machinery & equipment, and textiles.[16] These sectors have been chosen to represent approximatively the different sectors of Pavitt's taxonomy of industries (Pavitt, 1984); that is, science-based industries, scale-intensive industries, specialized supply industries, and supplier-dominated industries respectively. For these regressions we recalculate the multifactor productivity indicator at the level of each 2-digit

[16]These sectors are: NAF 33 (*Fabrication d'instruments médicaux, de précision, d'optique et d'horlogerie*), NAF 27 (*Métallurgie*), NAF 29 (*Fabrication de machines et d'équipements*) and NAF 17 (*Industrie textile*). For more details, see http://www.insee.fr/fr/nom_def_met/nomenclatures/naf/nlst60.htm.

sector.

The regression results are presented in Table 10. Although our results do show a certain degree of heterogeneity between the sectors, we generally observe results that are quite similar to those obtained from the preceding analysis.

The autocorrelation series are in line with previous work (Coad, 2007a, forthcoming). Firms in all sectors tend to experience a relatively large negative autocorrelation in GOS growth, and also a significant negative autocorrelation of productivity growth.

The results also suggest that employment growth is followed by sales growth, which in turn is followed by GOS growth. In all sectors there is a small but statistically significant feedback effect from sales growth to subsequent employment growth. In addition, there is evidence that employment growth contributes to a decrease in multifactor productivity growth (in the Machinery & Equipment sector).

6.4 Asymmetric effects for growing and shrinking firms

One potential caveat of the preceding analysis is that there may be asymmetric effects for growing and declining firms. For example, it may be relatively easy for firms to hire new employees while firing costs may limit their ability to lay workers off. In this section we therefore explore differential effects of the explanatory variables over the employment growth distribution. To do this, we perform quantile regressions, which are able to describe variation in the regression coefficient over the conditional employment growth quantiles. (For an introduction to quantile regression, see Koenker and Hallock (2001).)

To begin, we consider the autoregressive properties of productivity growth (see Figure 2). We observe that, for the 'average' firms at the central quantiles, there is a relatively small autocorrelation in productivity growth – of a magnitude of around -12%. There are more powerful forces of autocorrelation at the extreme quantiles, however. For firms with the fastest productivity growth at t, these firms are likely to have had relatively large productivity losses in the previous period. Figure 2 therefore presents evidence that those firms enjoying the highest productivity growth in any period are nonetheless not likely to maintain their productivity growth. Similarly, firms with productivity losses at t (at the lower quantiles of the plot) are likely to have enjoyed high productivity growth in the previous period. These results are likely to be sensitive to firm size, however – we would expect smaller firms to have relatively erratic productivity dynamics, whereas larger firms would presumably experience much smoother productivity growth (more on this in Coad, 2007a).

Figure 3 shows the relationship between productivity growth and subsequent employment growth. For the fastest growing firms at the upper quantiles, lagged productivity growth seems to make a significant positive contribution to subsequent employment growth. At the lower quantiles, however, job destruction seems to be independent of previous productivity growth. This could be due to rigidities in the labour market brought on by firing costs. In such cases, firms with declining productivity may be deterred from shedding jobs if such behavior entails additional firing costs.

For the sake of brevity, we do not present quantile regression results concerning other combinations of variables, because these have either been reported in other work (Coad, 2007a) or were deemed to be less interesting than the two cases presented above.[17]

7 Conclusion

The previous literature, reviewed above, did not provide conclusive results on the relationship between productivity and firm growth. Whilst theoretical approaches were in conflict, empirical work has often found no significant effect. Similarly, in this investigation we have often been unable to detect any strong relationship between firm growth and productivity growth.

[17]Further results on the analyses' robustness can be found in Coad and Broekel (2007).

Perhaps our most reliable result is that employment growth is negatively associated with the subsequent growth of multifactor productivity. In a variety of regression specifications, the coefficient is of a similar magnitude and statistically significant. Our estimates imply that an increase in employment growth of one percentage point is associated with a decrease in productivity growth of around 0.1 percentage points in the following year.[18] This negative association is still visible even after a two-year time lag. This result is in close agreement with the standard interpretation of 'Penrose effects' whereby managers must choose between pursuing growth opportunities (i.e. the training of new managers) or keeping operating costs down. This result is also in accordance with the notion of 'adjustment costs' facing growing firms. Although 'adjustment costs' are usually related to investment in fixed capital, it is also meaningful to speak of adjustment costs brought on by 'investment in human capital' (Cooper and Haltiwanger, 2006, p. 629). In this study we did not consider investment in fixed capital as a growth rate series, however, because of the peculiarities of working with such data.[19] This remains a challenge for future work.

Our analysis also indicates that annual growth rates of multifactor productivity, at the firm-level, are subject to significant negative autocorrelation. Firms that experienced high productivity growth in one year are unlikely to repeat this performance in the next year. Quantile autoregressions suggest that this negative correlation is particularly severe for those firms experiencing the most extreme growth in productivity in the previous year.

Our other results concerning systematic relationships between firm growth and productivity growth are less significant in both economic and statistical terms, and therefore should not receive undue emphasis. It would appear that productivity growth is associated with a rather small decrease in subsequent employment growth. Lagged productivity

[18] It should be reminded, however, that we are dealing only with net job creation/destruction. This corresponds to the net creation of positions in an organization, but carries no information on replacement of an old worker with a new one, or with the relocation of worker to a new position (although these latter effects presumably also have an influence on productivity growth).

[19] First, there are problems distinguishing between expansionary and replacement investment, which obscures the relationship between investment in fixed assets and firm growth. Second, there is a remarkable lumpiness in the time series of investment in fixed assets (Doms and Dunne, 1998) which complicates the econometric task of identification.

growth is also slightly positively associated with growth of profits. There is also some evidence that, if anything, sales growth is slightly positively associated with subsequent productivity growth.

This paper also yielded results that were consistently different across different measures of productivity – labour productivity or multifactor productivity. This discrepancy, we argued, is due to the fact that labour productivity does not control for changes in average wages or capital intensity.

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8 Appendix

The idea of the order-m approach is the following: (For an extensive introduction and discussion of its foundation, computation and application see Daraio and Simar (2007). For a multivariate case consider (x_0, y_0) as the inputs and outputs of the unit of interest. $(X_1, Y_1), ..., (X_m, Y_m)$ are the inputs and outputs of m randomly drawn other units that $Y_i \geq Y_0$. $\tilde{\theta}_m(x_0, y_0)$ measures the distance between point x_0 and the order-m frontier of $X_1, ..., X_m$. It can be written as:

$$\tilde{\theta}_m(x_0, y_0) = \underset{i=1,...,m}{min} \left\{ \underset{j=1,...,p}{max} \left(\frac{X_i^j}{x_0^j}\right) \right\} \tag{3}$$

with X_i^j (x_0^j) as the jth input of X_i (of x_0 respectively). The order-m efficiency measure of unit (x_0, y_0) is defined as

$$\theta_m(x_0, y_0) = E[\tilde{\theta}_m(x_0, y_0)|Y_i \geq y_0] \ . \tag{4}$$

It converges for $\lim_{m\to\infty}$ and $\lim_{n\to\infty}$ towards the traditional Free Disposal Hull (FDH) efficiency measure, where n is the total number of units.[20]. In order to calculate the order-m frontiers Cazals et al. (2002) suggest to employ a Monte-Carlo approximation with 200 replications which is followed here.

Changes in firms' order-m performance can be evaluated using the Malmquist index. An the input-oriented order-m Malmquist index measures the "productivity change relative to (the conical hull of) the frontier of the expected production set of order-m $(\mathcal{P}_m^t)$... " (Wheelock and Wilson, 2003, p. 12) and it can be written as[21]:

$$\mathcal{M}_m(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_1}, \mathcal{P}_m^{t_1}) = \left[\frac{D(x^{t_1}, y^{t_1}|\mathcal{V}(\mathcal{P}_m^{t_1}))}{D(x^{t_2}, y^{t_2}|\mathcal{V}(\mathcal{P}_m^{t_1}))} \times \frac{D(x^{t_1}, y^{t_1}|\mathcal{V}(\mathcal{P}_m^{t_2}))}{D(x^{t_2}, y^{t_2}|\mathcal{V}(\mathcal{P}_m^{t_2}))}\right]^{\frac{1}{2}} \tag{5}$$

[20]Note that the FDH like set-up takes into account variable returns to scale.

[21]Please note that Wheelock and Wilson (2003) use the Malmquist index for the output-orientation. However, the transformation to the input-orientation is straightforward.

whereby x^{t_1}, y^{t_1} is the input and output of a firm, $D(x^{t_1}, y^{t_1}|\mathcal{V}(\mathcal{P}_m^{t_1})$ the Shephard order-m input distance function, and $\mathcal{V}(\mathcal{P}_m^{t_1})$ defines the convex cone of the production set (technology) in period t_1, period t_2 respectively (see Wheelock and Wilson, 2003).

In order to analyze in more detail how a firms' performance changed over time, it is common to decompose the index into a number of components (see for an overview Zofio, 2006). Here we follow Wheelock and Wilson (2003) in decomposing the order-m Malmquist index into four parts.

$$\mathcal{M}_m(x^{t_1}, y^{t_1}, x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_1}, \mathcal{P}_m^{t_2}) = \underbrace{\left(\frac{D(x^{t_1}, y^{t_1}|\mathcal{P}_m^{t_1})}{D(x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_2})}\right)}_{=\triangle M\_Eff} \times$$
$$\underbrace{\left(\frac{D(x^{t_1}, y^{t_1}|\mathcal{V}(\mathcal{P}_m^{t_1}))/D(x^{t_1}, y^{t_1}|\mathcal{P}_m^{t_1})}{D(x^{t_2}, y^{t_2}|\mathcal{V}(\mathcal{P}_m^{t_2}))/D(x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_2})}\right)}_{=\triangle M\_SEff} \times \underbrace{\left(\frac{D(x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_2})}{D(x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_1})} \times \frac{D(x^{t_1}, y^{t_1}|\mathcal{P}_m^{t_2})}{D(x^{t_1}, y^{t_1}|\mathcal{P}_m^{t_1})}\right)^{\frac{1}{2}}}_{=\triangle M\_Fron} \times$$
$$\underbrace{\left\{\left[\frac{D(x^{t_1}, y^{t_1}|\mathcal{V}(\mathcal{P}_m^{t_2}))/D(x^{t_1}, y^{t_1}|\mathcal{P}_m^{t_2})}{D(x^{t_1}, y^{t_1}|\mathcal{V}(\mathcal{P}_m^{t_1}))/D(x^{t_1}, y^{t_1}|\mathcal{P}_m^{t_1})}\right] \times \left[\frac{D(x^{t_2}, y^{t_2}|\mathcal{V}(\mathcal{P}_m^{t_2}))/D(x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_2})}{D(x^{t_2}, y^{t_2}|\mathcal{V}(\mathcal{P}_m^{t_1}))/D(x^{t_2}, y^{t_2}|\mathcal{P}_m^{t_1})}\right]\right\}^{\frac{1}{2}}}_{=\triangle M\_SFron} \quad (6)$$

$\triangle M\_Eff$ is the measure of the change in the order-m technical efficiency. It shows whether the firm was able to decrease / increase its technological gap (catching-up or falling behind) to the order-m best-practice firms. $\triangle M\_SEff$ is an estimate a firm's change in the order-m scale efficiency. It indicates whether a firm increased its performance because of a change in its size that allows it to benefit (or not) from economies of scale. $\triangle M\_Fron$ represents the change in the order-m frontier between the two points in time and $\triangle M\_SFron$ captures the effect of economies of scale on the order-m frontier (see for a more detailed discussion Wheelock and Wilson, 2003).

In the present paper, our data covers only firms with more than 20 employees. Hence our sample does not cover the complete firm size distribution and thereby, an evaluation economies of scale effects seems to be of little use. The mix of firms of different industries (in which scale effects differ strongly) moreover does not warrant the inclusion of effect in the obtained efficiency scores. Therefore, the change in performance caused by economies of scale, represented by $\triangle M\_SEff$ and $\triangle M\_SFron$, is not considered here. A similar rationale can be applied to the measure of the change in the location of the frontier $\triangle M\_Fron$. In order to change its location a great number of firms has to change its performance levels. Such is likely the case to economy or industry wide effects or shocks. Both effects are rather uninteresting in our setting. Thus, $\triangle M\_Fron$ also seems to be of little importance for our investigation.

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Table 1: Summary stats concerning the size of firms (Sales given in FF for 1996 and 2000, and in Euros for 2004)

	Mean	Std. Dev.	10%	25%	Median	75%	90%	obs.
1996								
Sales	116768.3	751697.2	12538	18962	32752	74934	203322	6715
Empl	112.6673	396.5773	26	33	46	92	206	6715
2000								
Sales	147196.7	973241.8	14873	23081	41433	92790	255053	6715
Empl	117.376	387.9382	27	35	48	100	217	6715
2004								
Sales	24962.67	202849.7	2165	3545	6651	14963	40763	6715
Empl	115.9573	390.0338	26	34	48	99	214	6715

Table 2: Summary statistics of the growth rate series.

	Mean	Std. Dev.	10%	25%	Median	75%	90%	obs.
1997								
gr empl	0.0000	0.1264	-0.1000	-0.0426	-0.0098	0.0402	0.1080	6715
gr sales	0.0000	0.2060	-0.1686	-0.0715	-0.0032	0.0769	0.1774	6715
gr gos	0.0000	0.7786	-0.7463	-0.3058	0.0029	0.3089	0.7393	5900
gr prod	0.0000	0.3068	-0.3177	-0.1723	-0.0061	0.1159	0.2987	6715
2000								
gr empl	0.0000	0.1237	-0.1142	-0.0532	-0.0099	0.0462	0.1270	6715
gr sales	0.0000	0.1791	-0.1612	-0.0757	-0.0042	0.0757	0.1737	6715
gr gos	0.0000	0.7743	-0.7217	-0.2856	0.0000	0.3075	0.7152	5862
gr prod	0.0000	0.2421	-0.2621	-0.1340	-0.0164	0.1000	0.2796	6715
2004								
gr empl	0.0000	0.1208	-0.1107	-0.0364	0.0145	0.0469	0.1018	6715
gr sales	0.0000	0.1979	-0.1701	-0.0716	0.0008	0.0790	0.1717	6715
gr gos	0.0000	0.8275	-0.8109	-0.3065	0.0124	0.3153	0.8102	5069
gr prod	0.0000	0.2454	-0.1831	-0.0909	-0.0265	0.0541	0.1901	6715

Table 3: Correlation matrix for the indicators of firm growth. Conventional correlation coefficients are presented first, followed by Spearman's rank correlation coefficients.

	Empl. growth	Sales growth	GOS growth	Prod. growth
Empl. growth	1.0000			
p-value	0.0000			
obs	53720	-	-	-
Empl. gr. (Sp. rank)	1.0000			
p-value	0.0000			
Sales growth	0.3646	1.0000		
p-value	0.0000	0.0000		
obs	53720	53720	-	-
Sales gr. (Sp. rank)	0.327	1.0000		
p-value	0.0000	0.0000		
GOS growth	0.0671	0.3917	1.0000	
p-value	0.0000	0.0000	0.0000	
obs	45420	45420	45420	-
GOS gr. (Sp. rank)	0.0710	0.4757	1.0000	
p-value	0.0000	0.0000	0.0000	
Prod. growth	-0.1073	0.0783	0.1470	1.0000
p-value	0.0000	0.0000	0.0000	0.0000
obs	53720	53720	45420	53720
Prod. gr. (Sp. rank)	-0.1026	0.0936	0.1795	1.0000
p-value	0.0000	0.0000	0.0000	0.0000

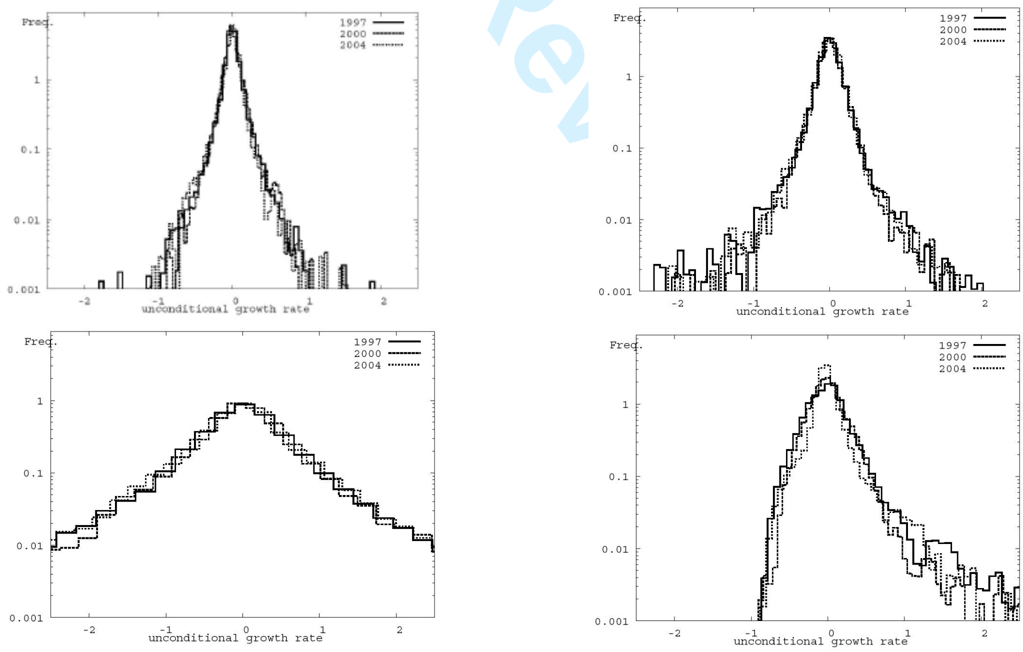

Figure 1: Distribution of the unconditional growth rates of our sample of French manufacturing firms. Top left: employment growth. Top right: sales growth. Bottom left: growth of gross operating surplus. Bottom right: growth of multifactor productivity. Note the log scale on the y axis.

Table 4: OLS estimation of equation (2). Coefficients significant at the 5% level appear in bold.

w_t	β_{t-1}				β_{t-2}					
	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	R^2	obs
Empl. gr.	**-0.1230**	**0.0485**	**0.0023**	0.0037					0.1085	37800
t-stat	-8.80	5.90	2.38	1.70						
Sales gr.	**0.1481**	**-0.2382**	**0.0078**	**0.0090**					0.0428	40351
t-stat	8.57	-14.85	5.01	2.91						
GOS gr.	0.0170	**0.2004**	**-0.3565**	**0.0436**					0.0154	40351
t-stat	0.43	5.27	-31.10	3.60						
Prod. gr.	**-0.1026**	0.0180	0.0026	**-0.2812**					0.0819	40351
t-stat	-6.96	1.56	1.18	-39.40						
Empl. gr.	**-0.1221**	**0.0659**	**0.0042**	0.0025	**-0.0189**	**0.0358**	**0.0036**	-0.0019	0.0189	33000
t-stat	-7.74	7.01	3.68	1.02	-1.96	4.77	3.12	-0.96		
Sales gr.	**0.1896**	**-0.2535**	**0.0111**	**0.0100**	**0.1019**	**-0.1162**	**0.0061**	0.0008	0.0469	33000
t-stat	9.18	-13.70	5.78	2.90	6.62	-8.28	3.39	0.25		
GOS gr.	0.0665	**0.3454**	**-0.4540**	**0.0625**	-0.0025	**0.1192**	**-0.2037**	0.0212	0.1405	30890
t-stat	1.56	8.05	-35.39	4.75	-0.06	3.17	-19.19	1.72		
Prod. gr.	**-0.1132**	**0.0299**	0.0013	**-0.3469**	**-0.0898**	**0.0303**	-0.0032	**-0.1690**	0.1246	33000
t-stat	-7.20	2.33	0.51	-40.89	-4.86	2.32	-1.17	-27.71		

Table 5: Bootstrapped LAD estimation of equation (2). Standard errors (and thus t-statistics) are obtained after 500 bootstrap replications. Coefficients significant at the 5% level appear in bold.

w_t	β_{t-1}				β_{t-2}					
	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	R^2	obs
Empl. gr.	**0.0080**	**-0.0061**	**0.0028**	-0.0014					0.0016	40351
t-stat	2.42	-8.55	4.26	-1.33						
Sales gr.	**0.0867**	**-0.0067**	-0.0004	-0.0019					0.0035	40351
t-stat	11.38	-4.52	-0.44	-1.17						
GOS gr.	-0.0222	**0.2729**	**-0.2914**	**0.0147**					0.0340	37800
t-stat	-0.82	25.58	-30.53	2.19						
Prod. gr.	**-0.1039**	**0.0174**	**-0.0054**	**-0.1135**					0.0178	40351
t-stat	-8.79	8.49	-3.86	-30.96						
Empl. gr.	**0.0130**	**-0.0071**	**0.0043**	**-0.0026**	**0.0285**	**-0.0087**	**0.0026**	-0.0022	0.0043	33000
t-stat	2.90	-8.76	5.76	-2.35	6.03	-11.64	4.40	-1.64		
Sales gr.	**0.1055**	**-0.0064**	0.0001	-0.0008	**0.0439**	-0.0044	-0.0017	**-0.0040**	0.0052	33000
t-stat	10.84	-4.12	0.05	-0.47	5.95	-3.02	-1.54	-2.16		
GOS gr.	0.0224	**0.3413**	**-0.3614**	**0.0249**	-0.0054	**0.1374**	**-0.1505**	**0.0146**	0.0473	30890
t-stat	0.67	31.48	-35.55	3.04	-0.19	14.45	-18.06	1.96		
Prod. gr.	**-0.0856**	**0.0203**	**-0.0073**	**-0.1386**	**-0.0433**	-0.0009	**-0.0039**	**-0.0622**	0.0270	33000
t-stat	-6.65	8.57	-4.64	-29.67	-4.31	-0.39	-2.08	-17.30		

Table 6: Bootstrapped LAD estimation of equation (2). Standard errors (and thus t-statistics) are obtained after 500 bootstrap replications. Productivity growth is measured using growth of labour productivity. Coefficients significant at the 5% level appear in bold.

w_t	β_{t-1}				β_{t-2}					
	Empl. gr.	Sales gr.	GOS gr.	Lab. Prod. gr.	Empl. gr.	Sales gr.	GOS gr.	Lab. Prod. gr.	R^2	obs
Empl. gr.	-0.0029	0.0040	**0.0038**	**-0.0112**					0.0018	40351
t-stat	-0.76	1.61	6.72	-4.14						
Sales gr.	**0.1614**	**-0.0743**	**-0.0059**	**0.0738**					0.0055	40351
t-stat	13.05	-10.06	-4.98	9.34						
GOS gr.	**0.1593**	**0.1050**	**-0.3092**	**0.1878**					0.0347	37800
t-stat	3.90	3.62	-33.74	5.86						
Lab. Prod. gr.	**0.0797**	**0.0612**	**-0.0184**	**-0.0476**					0.0104	40351
t-stat	5.78	7.55	-13.09	-5.73						
Empl. gr.	-0.0056	**0.0107**	**0.0059**	**-0.0199**	**0.0216**	-0.0021	**0.0033**	**-0.0079**	0.0047	33000
t-stat	-1.09	3.22	6.83	-5.37	3.45	-0.70	4.95	-2.43		
Sales gr.	**0.1709**	**-0.0679**	**-0.0047**	**0.0665**	**0.0660**	**-0.0244**	**-0.0038**	**0.0235**	0.0066	33000
t-stat	13.09	-7.60	-3.11	7.04	7.32	-3.80	-2.66	3.41		
GOS gr.	**0.2276**	**0.1579**	**-0.3873**	**0.2144**	-0.0329	**0.1474**	**-0.1529**	-0.0039	0.0481	30890
t-stat	4.71	5.13	-28.61	5.67	-0.83	5.66	-14.93	-0.13		
Lab. Prod. gr.	**0.0708**	**0.0852**	**-0.0231**	**-0.0664**	-0.0131	**0.0506**	**-0.0128**	**-0.0433**	0.0143	33000
t-stat	4.53	9.21	-14.26	-6.95	-1.07	6.43	-9.59	-5.26		

Table 7: Bootstrapped LAD estimation of equation (2) across 5 approximately equipopulated size groups. Firms are sorted into size groups according to their average size (i.e. mean number of employees 1996-2004). Standard errors (and hence t-statistics) obtained from using 500 bootstrap replications. Coefficients significant at the 5% level appear in bold.

w_t	β_{t-1}					
	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	R^2	obs
Smallest 20%						
Empl. gr.	**-0.0740**	**-0.0122**	**0.0048**	-0.0021	0.0095	8035
t-stat	-4.55	-7.16	3.38	-0.44		
Sales gr.	**0.0388**	**-0.0090**	-0.0004	-0.0067	0.0018	8035
t-stat	2.16	-2.41	-0.19	-0.96		
GOS gr.	-0.0576	**0.2666**	**-0.2771**	-0.0203	0.0349	7491
t-stat	-0.80	10.34	-12.11	-0.93		
Prod. gr.	**-0.0575**	**0.0274**	**-0.0093**	**-0.0967**	0.0181	8035
t-stat	-2.75	8.78	-5.17	-10.66		
20-40%						
Empl. gr.	**-0.0426**	**-0.0033**	**0.0025**	**-0.0068**	0.0028	8205
t-stat	-3.01	-2.31	2.12	-3.90		
Sales gr.	**0.0781**	-0.0026	**-0.0042**	0.0037	0.0033	8205
t-stat	4.28	-0.87	-2.25	0.79		
GOS gr.	0.0336	**0.3162**	**-0.3173**	0.0166	0.0399	7683
t-stat	0.50	12.20	-13.67	1.24		
Prod. gr.	**-0.0943**	**0.0303**	**-0.0053**	**-0.1074**	0.0245	8205
t-stat	-3.73	8.83	-2.16	-15.96		
40-60%						
Empl. gr.	-0.0026	**-0.0044**	0.0007	**-0.0044**	0.0020	8158
t-stat	-0.36	-4.62	0.91	-2.71		
Sales gr.	**0.0709**	-0.0040	-0.0004	**-0.0123**	0.0029	8158
t-stat	3.55	-1.04	-0.16	-3.28		
GOS gr.	**-0.1489**	**0.2873**	**-0.3031**	0.0163	0.0371	7683
t-stat	-2.47	15.09	-16.53	1.52		
Prod. gr.	**-0.1590**	**0.0400**	**-0.0098**	**-0.1094**	0.0270	8158
t-stat	-6.28	7.56	-2.46	-19.75		
60-80%						
gr empl	**0.0782**	**-0.0065**	**0.0041**	0.0005	0.0053	7980
t-stat	4.39	-3.41	3.00	0.19		
Sales gr.	**0.1191**	**-0.0073**	0.0007	0.0021	0.0058	7980
t-stat	6.51	-2.52	0.31	0.53		
GOS gr.	-0.0154	**0.2797**	**-0.3011**	0.0339	0.0361	7426
t-stat	-0.26	11.65	-13.93	1.68		
Prod. gr.	**-0.1424**	**0.0533**	-0.0071	**-0.1233**	0.0232	7980
t-stat	-4.76	6.76	-1.53	-13.60		
Largest 20%						
gr empl	**0.1647**	**-0.0056**	**0.0036**	0.0029	0.0175	7973
t-stat	8.40	-3.71	3.37	1.21		
Sales gr.	**0.1576**	**-0.0116**	**0.0036**	0.0020	0.0087	7973
t-stat	6.76	-4.95	2.21	0.61		
gr gos	0.0594	**0.1804**	**-0.2240**	0.0069	0.0244	7517
t-stat	1.17	7.12	-10.01	0.43		
Prod. gr.	-0.0342	**-0.0716**	**0.0123**	**-0.1766**	0.0279	7973
t-stat	-1.52	-6.68	2.43	-12.31		

Table 8: Bootstrapped LAD estimation of equation (2) across 5 approximately equipopulated size groups. Firms are sorted into size groups according to their initial size (Sales in 1996). Standard errors (and hence t-statistics) obtained from using 500 bootstrap replications. Coefficients significant at the 5% level appear in bold.

w_t	β_{t-1}					
	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	R^2	obs
Smallest 20%						
Empl. gr.	**-0.0451**	**-0.0058**	**0.0049**	-0.0110	0.0030	7899
t-stat	-3.5	-2.85	3.69	-1.83		
Sales gr.	**0.0938**	-0.0028	-0.0017	**-0.0174**	0.0043	7899
t-stat	5.64	-0.88	-0.87	-2.33		
GOS gr.	0.1198	**0.3386**	**-0.3100**	-0.0121	0.0389	7281
t-stat	1.74	13.17	-14.46	-0.45		
Prod. gr.	**-0.1122**	**0.0124**	**-0.0079**	-0.0910	0.0147	7899
t-stat	-6.2	5.16	-4.42	-10.17		
20-40%						
Empl. gr.	**-0.0308**	**-0.0031**	0.0013	**-0.0048**	0.0018	8216
t-stat	-2.85	-2.31	1.17	-1.99		
Sales gr.	**0.0743**	**-0.0072**	-0.0016	-0.0101	0.0032	8216
t-stat	4.03	-2.05	-0.67	-1.89		
GOS gr.	**-0.1729**	**0.2843**	**-0.2958**	0.0037	0.0351	7726
t-stat	-2.73	12.97	-14.19	0.27		
Prod. gr.	**-0.1443**	**0.0452**	**-0.0104**	**-0.1080**	0.0342	8216
t-stat	-5.77	12.52	-3.41	-17.16		
40-60%						
Empl. gr.	-0.0022	**-0.0070**	**0.0039**	-0.0011	0.0018	8144
t-stat	-0.28	-5.35	3.07	-0.54		
Sales gr.	**0.0708**	-0.0039	-0.0031	0.0012	0.0025	8144
t-stat	3.31	-1.06	-1.13	0.38		
GOS gr.	0.0558	**0.2606**	**-0.2851**	**0.0209**	0.0360	7655
t-stat	0.82	11.68	-15.56	2.04		
Prod. gr.	**-0.2008**	**0.0633**	**-0.0104**	**-0.1059**	0.0334	8144
t-stat	-7.24	10.81	-2.69	-17.05		
60-80%						
Empl. gr.	0.0205	**-0.0059**	0.0024	-0.0028	0.0015	8003
t-stat	1.62	-4.20	1.87	-1.35		
Sales gr.	**0.0760**	**-0.0060**	-0.0011	-0.0011	0.0030	8003
t-stat	4.71	-1.99	-0.49	-0.25		
GOS gr.	-0.0906	**0.2932**	**-0.3262**	0.0184	0.0431	7479
t-stat	-1.72	12.24	-15.07	1.12		
Prod. gr.	**-0.0551**	0.0115	0.0035	**-0.1298**	0.0167	8003
t-stat	-1.99	1.30	0.62	-10.13		
Largest 20%						
Empl. gr.	**0.1664**	**-0.0062**	**0.0034**	0.0041	0.0180	8089
t-stat	8.63	-4.32	3.21	1.83		
Sales gr.	**0.1279**	**-0.0116**	0.0028	0.0024	0.0071	8089
t-stat	4.90	-5.00	1.62	0.77		
GOS gr.	0.0357	**0.1725**	**-0.2170**	0.0116	0.0222	7659
t-stat	0.51	6.83	-9.19	0.72		
Prod. gr.	-0.0238	**-0.0593**	**0.0112**	**-0.1885**	0.0296	8089
t-stat	-1.00	-7.97	2.74	-11.82		

Table 9: Bootstrapped LAD estimation of equation (2) for individual years. Standard errors (and hence t-statistics) obtained from using 500 bootstrap replications. Coefficients significant at the 5% level appear in bold.

w_t	β_{t-1}					
	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	R^2	obs
1998						
Empl. gr.	-0.0156	**0.0467**	0.0021	-0.0036	0.0052	5900
t-stat	-1.01	4.63	1.92	-1.05		
Sales gr.	**0.0948**	**-0.0923**	-0.0013	**-0.0099**	0.0076	5900
t-stat	3.88	-4.44	-0.43	-2.16		
GOS gr.	-0.0208	0.1165	**-0.2597**	-0.0234	0.0364	5690
t-stat	-0.33	1.66	-12.21	-1.10		
Prod. gr.	**-0.1111**	0.0495	-0.0094	-0.0286	0.0017	5900
t-stat	-2.60	1.51	-1.69	-1.85		
2000						
Empl. gr.	-0.0071	**0.0833**	0.0000	0.0005	0.0110	5928
t-stat	-0.47	8.46	0.02	0.23		
Sales gr.	**0.1587**	**-0.0740**	0.0007	0.0034	0.0065	5928
t-stat	5.26	-3.21	0.23	1.06		
GOS gr.	0.0608	**0.2688**	**-0.2974**	**0.0456**	0.0371	5659
t-stat	0.86	3.37	-10.52	3.68		
Prod. gr.	**-0.0654**	**-0.0441**	**-0.0119**	**-0.0695**	0.0251	5928
t-stat	-2.34	-2.72	-2.82	-13.71		
2002						
Empl. gr.	0.0000	0.0000	0.0000	0.0000	0.0000	5842
t-stat	0.00	0.00	0.00	0.00		
Sales gr.	**0.0816**	**-0.0632**	0.0016	0.0040	0.0032	5842
t-stat	4.01	-3.20	0.59	0.48		
GOS gr.	-0.1138	**0.2262**	**-0.2977**	0.0481	0.0341	5389
t-stat	-1.31	2.28	-10.96	1.64		
Prod. gr.	**-0.0867**	-0.0316	0.0019	**-0.2360**	0.0275	5842
t-stat	-3.32	-1.73	0.53	-11.11		
2004						
Empl. gr.	-0.0055	**0.0411**	0.0015	0.0067	0.0026	5246
t-stat	-0.41	3.56	1.32	1.86		
Sales gr.	**0.1394**	**-0.0433**	0.0021	0.0064	0.0053	5246
t-stat	5.47	-2.18	0.83	0.78		
GOS gr.	-0.0645	**0.4131**	**-0.3379**	0.0394	0.0408	4800
t-stat	-0.74	5.32	-13.97	1.16		
Prod. gr.	**-0.1028**	-0.0140	-0.0037	**-0.1169**	0.0160	5246
t-stat	-4.84	-0.99	-1.52	-9.31		

Table 10: LAD estimation of equation (2) across different industries. Multifactor productivity has been calculated for each sector separately. Standard errors (and hence t-statistics) obtained from using 1000 bootstrap replications. Coefficients significant at the 5% level appear in bold.

w_t	β_{t-1}					
	Empl. gr.	Sales gr.	GOS gr.	Prod. gr.	R^2	obs
NAF 33: Instruments						
Empl gr	0.0541	**0.0787**	0.0027	-0.0111	0.0174	1437
t-stat	1.89	3.38	0.86	-0.57		
Sales gr	**0.1661**	-0.0330	-0.0007	-0.0040	0.0082	1437
t-stat	3.08	-0.70	-0.14	-0.13		
GOS gr	-0.0515	0.2994	**-0.2921**	-0.0719	0.0418	1327
t-stat	-0.26	1.59	-5.29	-0.54		
Prod gr	-0.0277	-0.0041	-0.0034	**-0.2118**	0.0268	1437
t-stat	-1.51	-0.30	-1.26	-5.18		
NAF 27: Primary metals						
Empl gr	0.0091	**0.0593**	0.0001	0.0034	0.0100	1042
t-stat	0.28	2.23	0.02	0.24		
Sales gr	0.0740	-0.0405	-0.0040	-0.0001	0.0053	1042
t-stat	0.83	-0.98	-0.90	0.00		
GOS gr	0.0771	-0.0622	**-0.2806**	-0.0407	0.0454	970
t-stat	0.45	-0.27	-3.73	-0.20		
Prod gr	0.0032	0.0359	-0.0026	**-0.2957**	0.0478	1042
t-stat	0.12	1.26	-0.70	-5.00		
NAF 29: Machinery and Equipment						
Empl gr	0.0033	**0.0401**	-0.0006	0.0043	0.0043	4119
t-stat	0.22	3.94	-0.37	0.61		
Sales gr	**0.1718**	**-0.2105**	0.0060	**0.0373**	0.0177	4119
t-stat	5.10	-7.33	1.61	2.68		
GOS gr	0.0971	0.1095	**-0.3310**	0.0485	0.0509	3806
t-stat	0.65	1.07	-9.32	0.71		
Prod gr	**-0.0507**	-0.0001	0.0041	**-0.3187**	0.0504	4119
t-stat	-3.17	-0.01	1.78	-11.28		
NAF 17: Textiles						
Empl gr	0.0034	**0.0710**	0.0038	-0.0007	0.0101	2184
t-stat	0.18	3.81	1.20	-0.18		
Sales gr	**0.0946**	0.0164	-0.0015	-0.0178	0.0042	2184
t-stat	2.53	0.55	-0.25	-1.84		
GOS gr	0.0355	**0.4001**	**-0.3155**	-0.0197	0.0322	2004
t-stat	0.27	3.38	-6.92	-0.56		
Prod gr	-0.0347	-0.0134	**0.0141**	**-0.2838**	0.0464	2184
t-stat	-0.74	-0.50	2.14	-7.34		

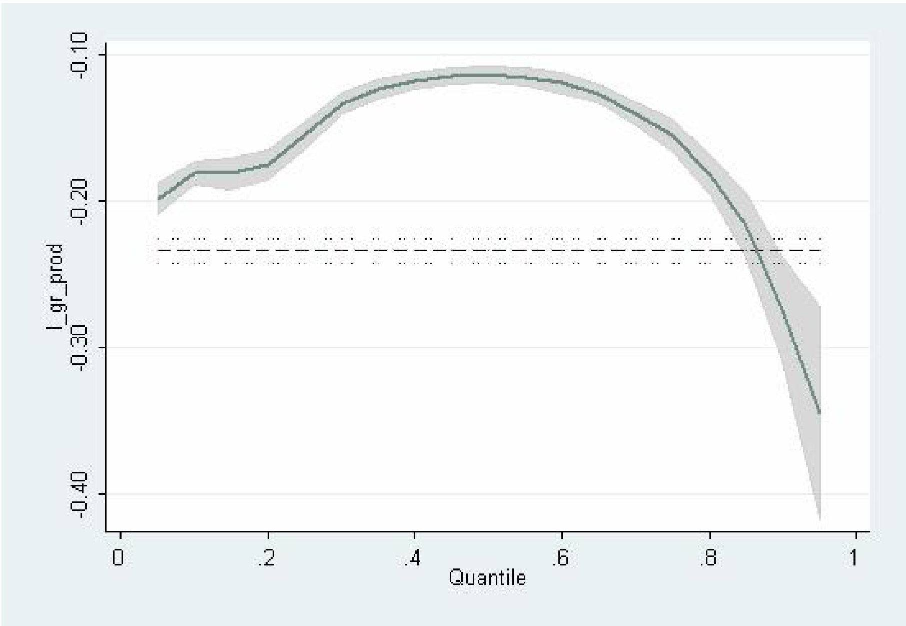

Figure 2: Quantile autoregression analysis of the relationship between productivity growth (t) and productivity growth ($t-1$). Variation in the coefficient on lagged growth of productivity over the conditional quantiles of the productivity growth rate distribution (at t). Conditional quantiles (on the x-axis) range from 0 (for the extreme negative-growth firms) to 1 (for the fastest-growing firms). Confidence intervals (non-bootstrapped) extend to 95% confidence intervals in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals (dotted lines). Graphs made using the 'grqreg' Stata module (Azevedo (2004)).

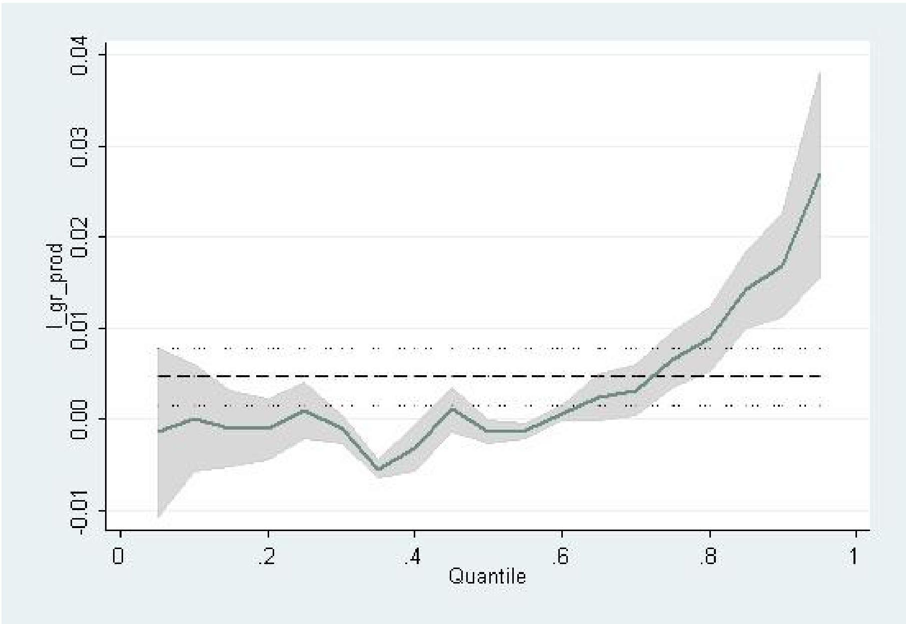

Figure 3: Quantile regression analysis of the relationship between employment growth (t) and productivity growth ($t-1$). Variation in the coefficient on lagged growth of productivity over the conditional quantiles of the employment growth rate distribution (at t). Conditional quantiles (on the x-axis) range from 0 (for the extreme negative-growth firms) to 1 (for the fastest-growing firms). Confidence intervals (non-bootstrapped) extend to 95% confidence intervals in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals (dotted lines).